

# Constrained Regularization for Lagrangian Actinometry

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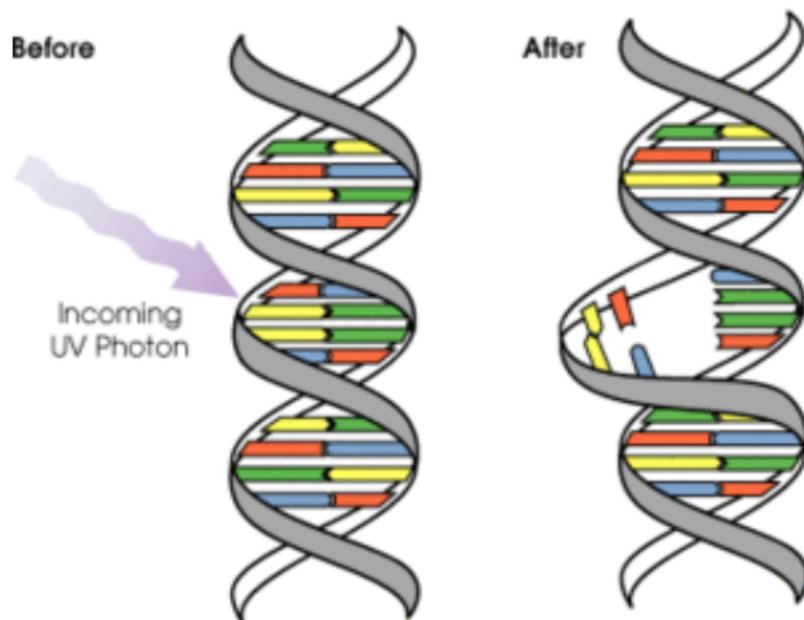
September 21, 2010

# UV Irradiation and Disinfection: UV Reactors



<http://water-technology.net/projects/sharjah>

# UV Irradiation and Disinfection



[http://em.wikipedia.org/wiki/Pyrimidine\\_dimers](http://em.wikipedia.org/wiki/Pyrimidine_dimers)

# UV Dose: Master Variable (Lagrangian = Particle Specific)

Integral

$$\text{Dose} = \int_0^t I(t) \cdot dt$$

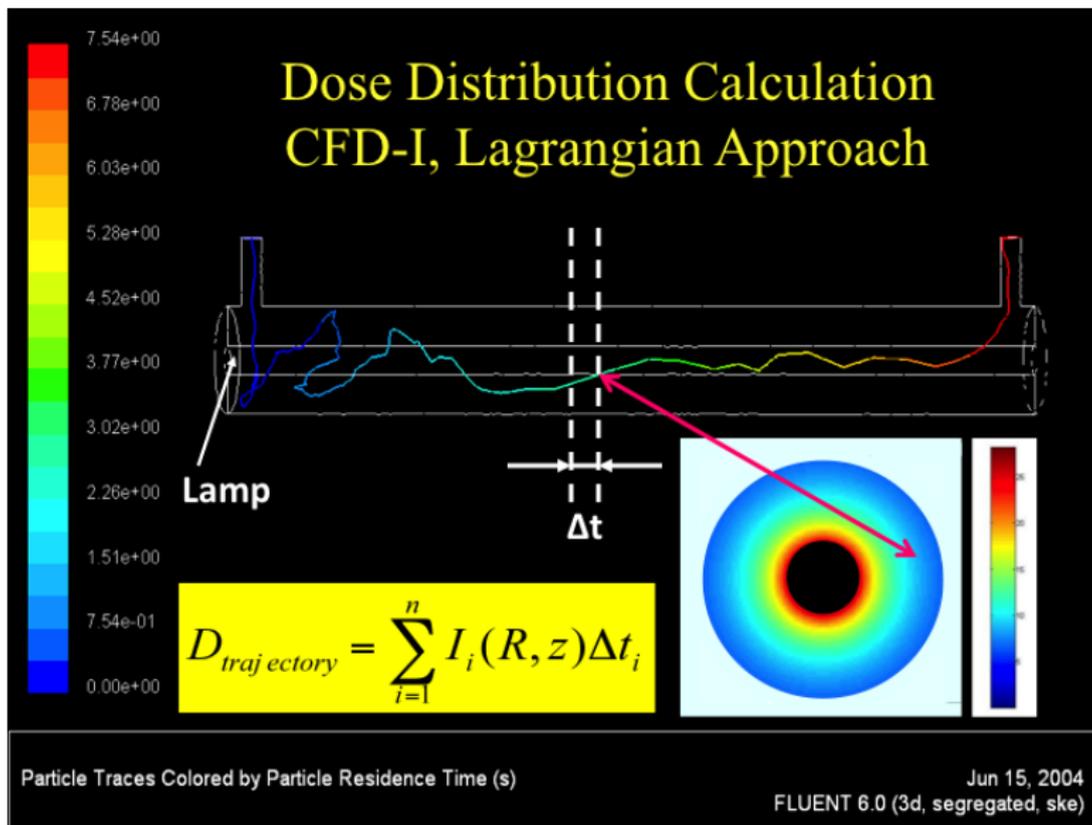
Discrete

$$\text{Dose} \approx \sum_{j=1}^n I_j(R, z) \cdot \Delta t_j$$

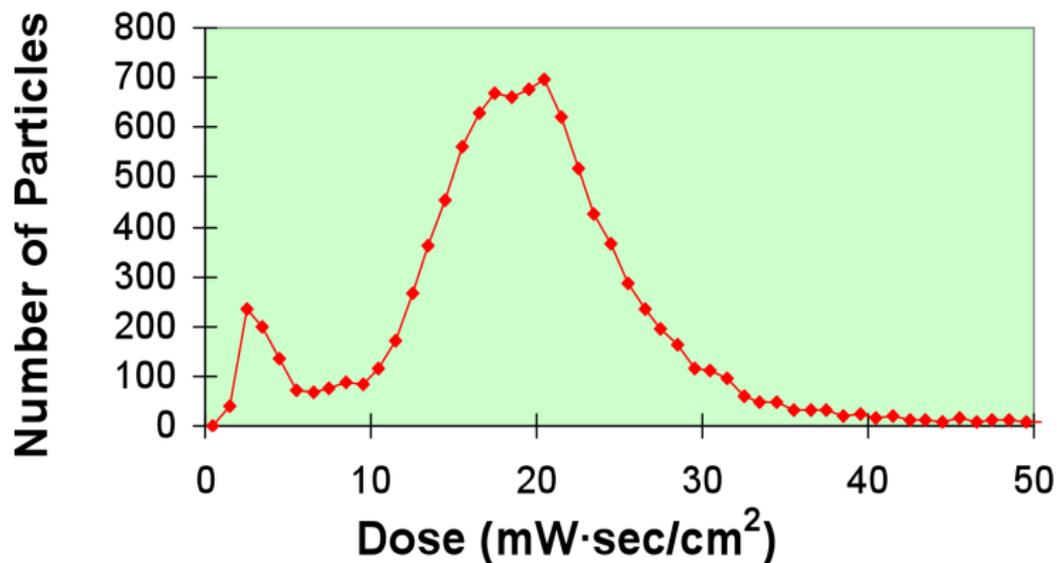
- ▶ Exposure Time
- ▶ Intensity Field
- ▶ Intensity History
- ▶ Particle Trajectory

# UV Dose Distributions: CFD-I Models

- ▶ Chiu, *et al.* [1] (Particle Tracking)
- ▶ Lyn and Blatchley [2] (CFD models for UV disinfection)
- ▶ J. Ducoste *et al.* [3] (Lagrangian vs. Eulerian)

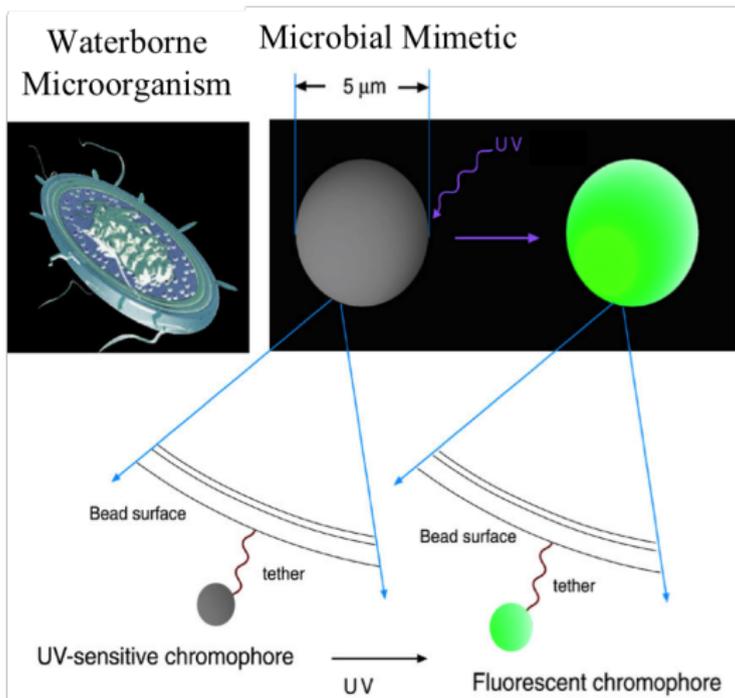


## Dose Distribution (Chiu *et al.* 1999 [1])



# Lagrangian Actinometry (LA): Dyed Microspheres

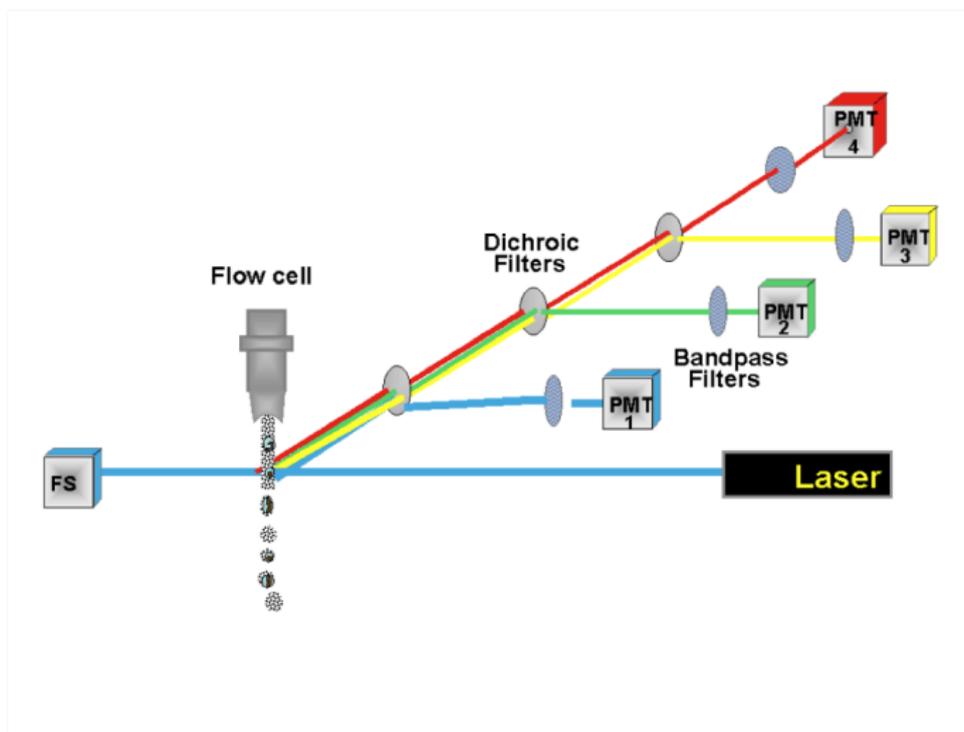
- ▶ Blatchley *et al.* [4]



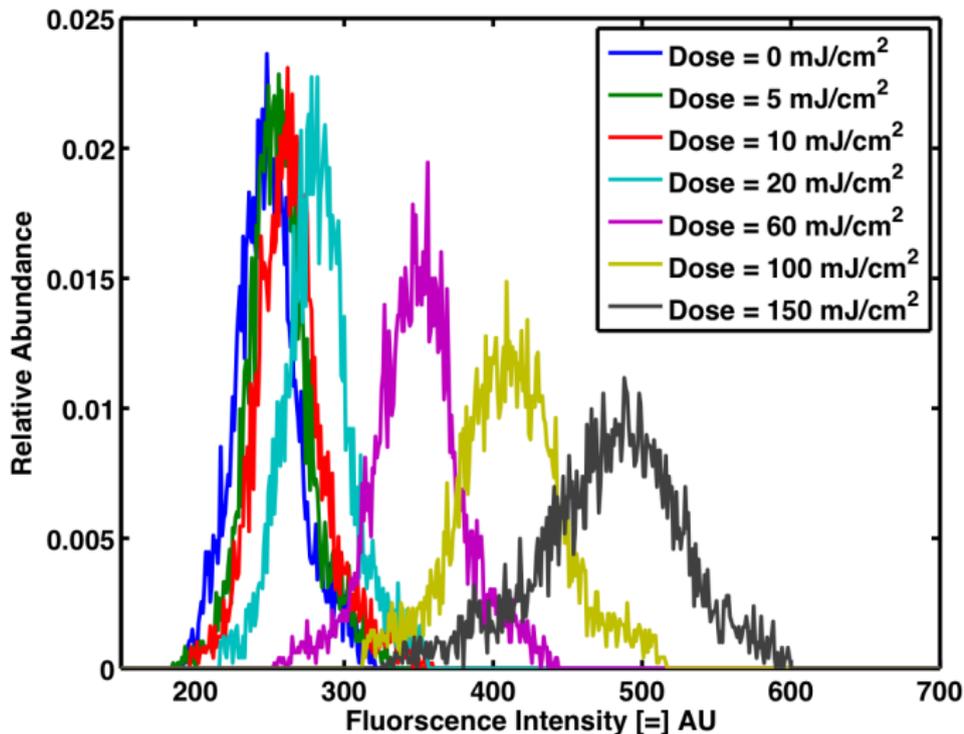
# Lagrangian Actinometry (LA): Dose-Response Calibration



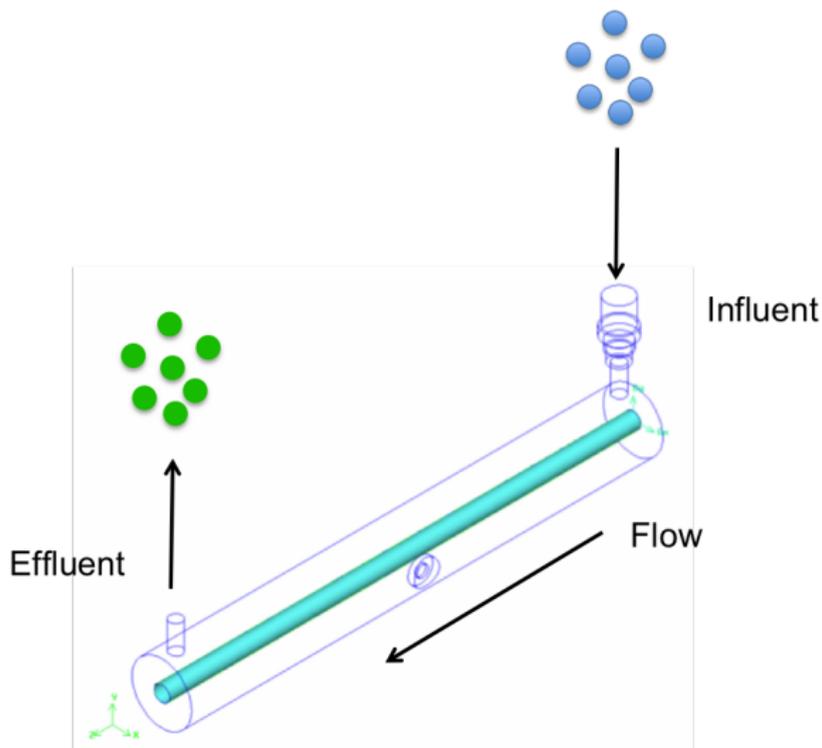
# Lagrangian Actinometry (LA): Flow Cytometry [5]



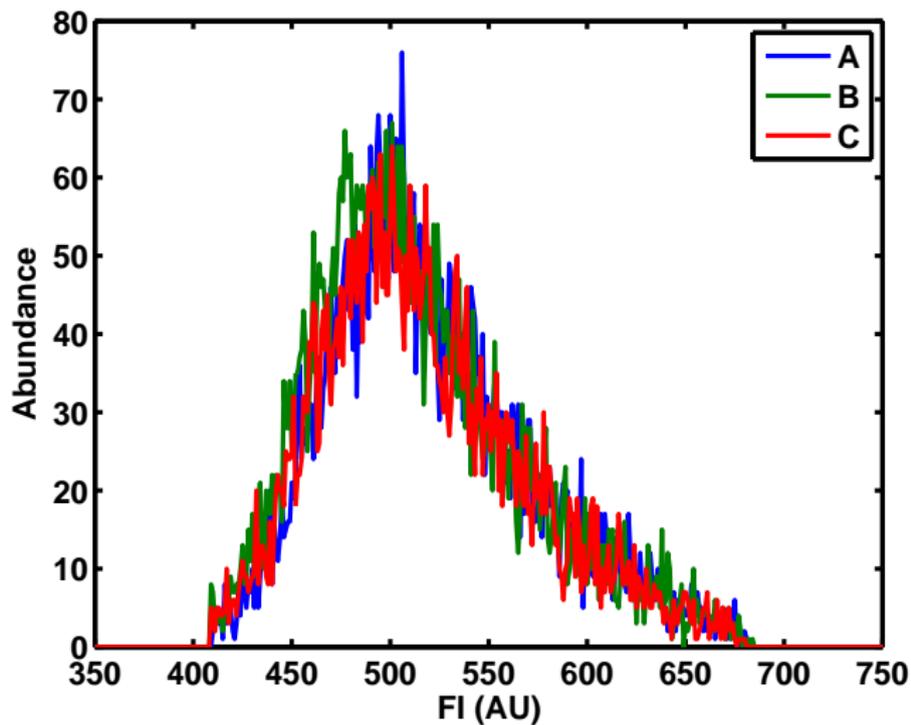
# Lagrangian Actinometry (LA): Dose-Response Calibration



# Lagrangian Actinometry (LA): UV Reactor Experiment



# Lagrangian Actinometry (LA): UV Reactor FI Distributions

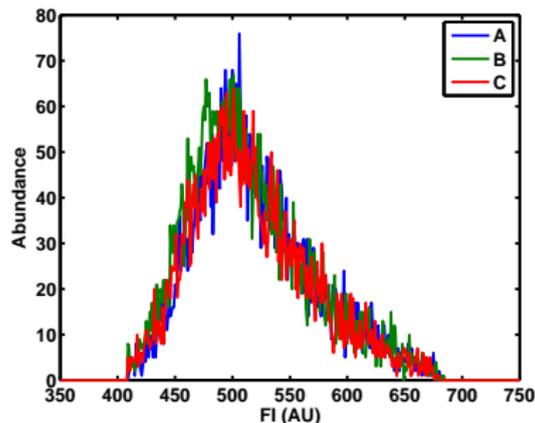
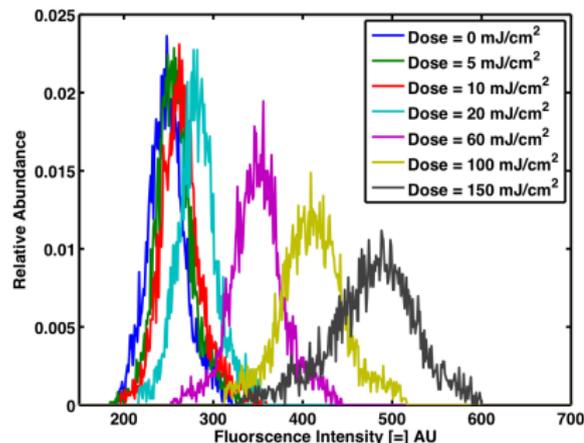


# Lagrangian Actinometry (LA): Linear Equations

## Linear Combination [4]

$$k_{i1}x_1 + k_{i2}x_2 + \dots + k_{in}x_n = y_i \quad (1)$$

with,  $i = 1, 2, \dots, m$ , FI channels. UV dose  $j = 1, 2, \dots, n$



# Lagrangian Actinometry: Linear Equations

## Linear Least-Squares Problem (linear model)

$$\mathbf{y} = K\mathbf{x} + \epsilon \quad (2)$$

with  $\mathbf{y} \in \mathbb{R}^m$ , measured reactor FI distribution,  $K \in \mathbb{R}^{m \times n}$ , dose-response calibration matrix,  $\mathbf{x} \in \mathbb{R}^n$  dose distribution,  $\epsilon \sim N(0, S^2)$  vector of measurement errors.

$$\mathbf{y} = \begin{pmatrix} | \\ | \\ | \\ | \\ | \end{pmatrix} \quad K = \begin{pmatrix} | & & & & \\ & | & & & \\ & & | & & \\ & & & | & \\ & & & & | \\ & & & & & | \\ & & & & & & | \end{pmatrix}$$

Historical Method

Regularization Method

Truncated SVD

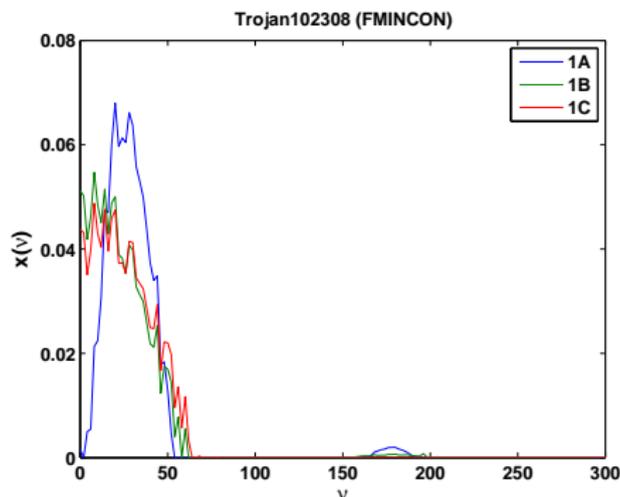
Constrained Regularization

Application to Large-scale UV reactors

# Constrained Minimization Method (FMINCON)

## Constrained Minimization Problem (FMINCON)

$$\min_{\mathbf{x}} \varphi(\mathbf{x}) = \|\mathbf{y} - \mathbf{K}\mathbf{x}\|_2^2 \quad \text{subject to} \quad \begin{cases} \mathbf{B}\mathbf{x} = \mathbf{d} \rightarrow \sum_i x_i = 1 \\ 0 \leq \mathbf{x} \leq 1 \end{cases} \quad (3)$$



- ▶ As of 2006, This Summarizes the Extent of Knowledge on Numerical Methods for LA.

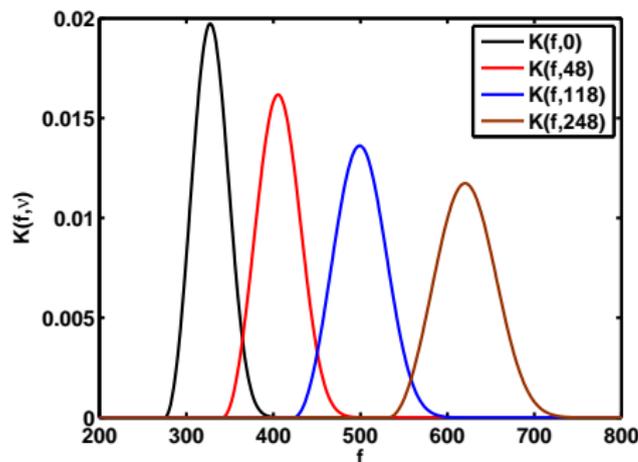
# Constrained Minimization Test Problem

**Objective: Determine if Solution is Stable Under Small Perturbations to  $y_{tr} = Kx^*$**

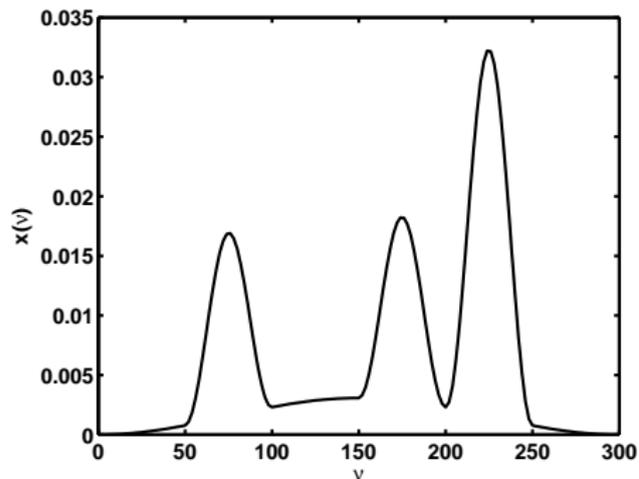
## Definitions

- ▶  $y_{tr} = Kx^*$ , with  $x^*$  is a “true solution”
- ▶  $y = Kx^* + \epsilon$ , with  $\epsilon$  being the perturbation to  $y_{tr}$

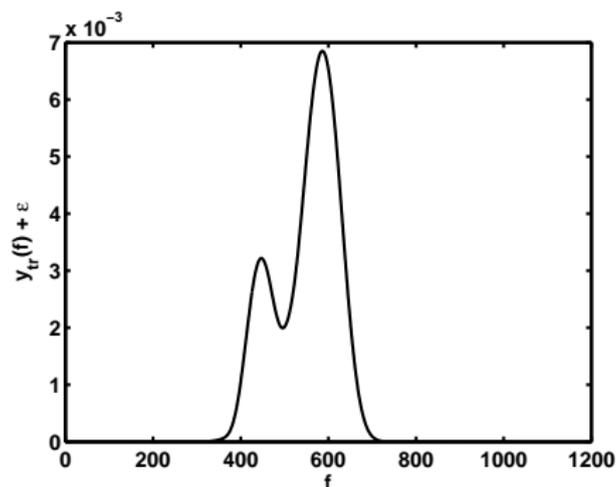
$K$  matrix



$x^*$  “true solution”



# Constrained Minimization Test Problem: Right-Hand Side



## Data Generation

$$\mathbf{y} = K\mathbf{x}^* + \epsilon \quad (4)$$

$$\epsilon \sim N(0, S^2) \quad (5)$$

with,  $S^2 = \text{diag}(s_1^2, s_2^2, \dots, s_m^2)$

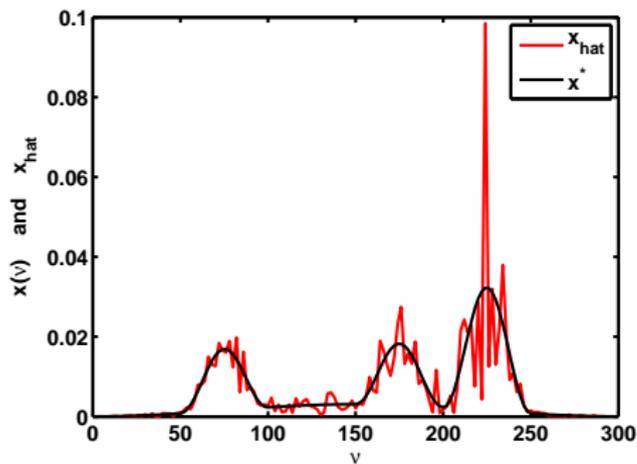
$$s_i = 10^{-5} \sqrt{y_{tr,i}} \quad (6)$$

# Scaled Solutions

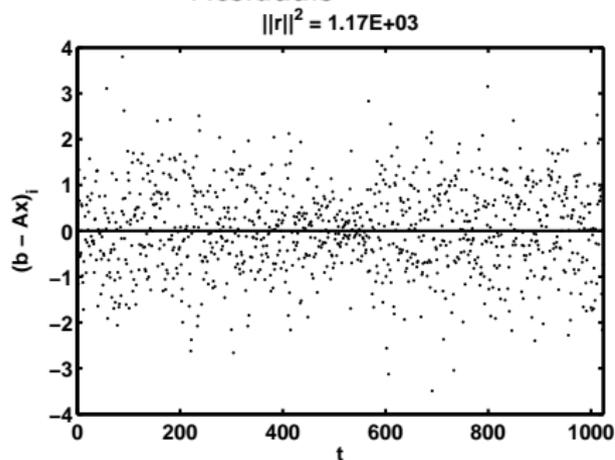
## Constrained Weighted Least-Squares

$$\min_{\mathbf{x} \geq 0} \varphi = \|S^{-1}(\mathbf{y} - K\mathbf{x})\|_2^2, \quad \mathbf{w}^T \mathbf{x} = 1 \quad (7)$$

Computed Solution,  $\hat{\mathbf{x}}$



Residuals



# Singular Value Decomposition (SVD) Characteristics

## Characteristics of Ill-Posed Problems (SVD) [10], [11]

1. The right singular vectors  $\mathbf{v}_j$  become more oscillatory as  $j$  increases.
  2. The singular values  $\sigma_j$  of  $A$  gradually decay to zero without a noticeable gap.
  3. The discrete Picard condition occurs.
- ▶ For problems with SVD characteristics above, truncated SVD is effective

# Singular Value Decomposition: SVD

## SVD

$$A = U \hat{\Sigma} V^T \quad (8)$$

$$A = U \begin{pmatrix} \Sigma \\ 0 \end{pmatrix} V^T, \quad \Sigma = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_n) \quad (9)$$

$A \in \mathbb{R}^{m \times n}$ ,  $U \in \mathbb{R}^{m \times m}$ ,  $\Sigma \in \mathbb{R}^{m \times n}$ , and  $V \in \mathbb{R}^{n \times n}$ .

## SVD Properties

- ▶  $\Sigma = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_n)$ ,  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n$ , and



$$U^T U = I_m = U U^T, \quad V^T V = I_n = V V^T \quad (10)$$

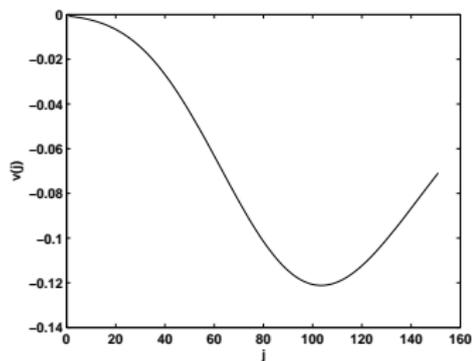
## SVD Least-Squares Solution

$$\min_{\mathbf{x} \in \mathbb{R}^n} \|\mathbf{b} - A\mathbf{x}\|_2^2 = \min_{\mathbf{x} \in \mathbb{R}^n} \left\| \begin{pmatrix} U_1^T \\ U_2^T \end{pmatrix} \mathbf{b} - \begin{pmatrix} \Sigma \\ 0 \end{pmatrix} V^T \mathbf{x} \right\|_2^2, \quad (11)$$

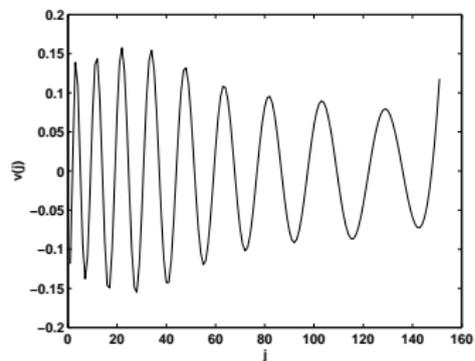
Note:  $U_1 \in \mathbb{R}^{n \times m}$ ,  $U_2 \in \mathbb{R}^{m-n \times m}$ .

$$V^T \hat{\mathbf{x}} = \Sigma^{-1} U_1^T \mathbf{b}, \quad \therefore \hat{\mathbf{x}} = V \mathbf{z} \quad (12)$$

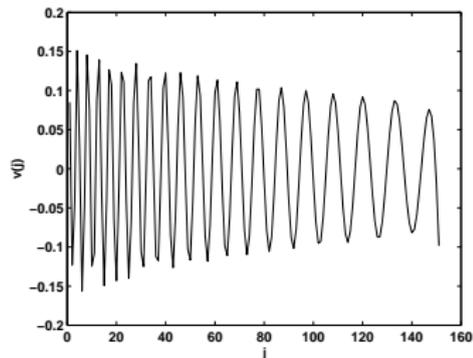
# Right Singular Vectors, $V$



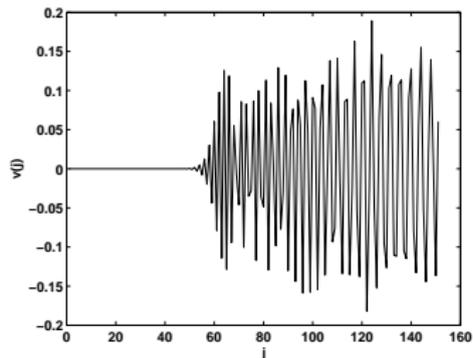
(a)  $\mathbf{v}_1$



(b)  $\mathbf{v}_{20}$

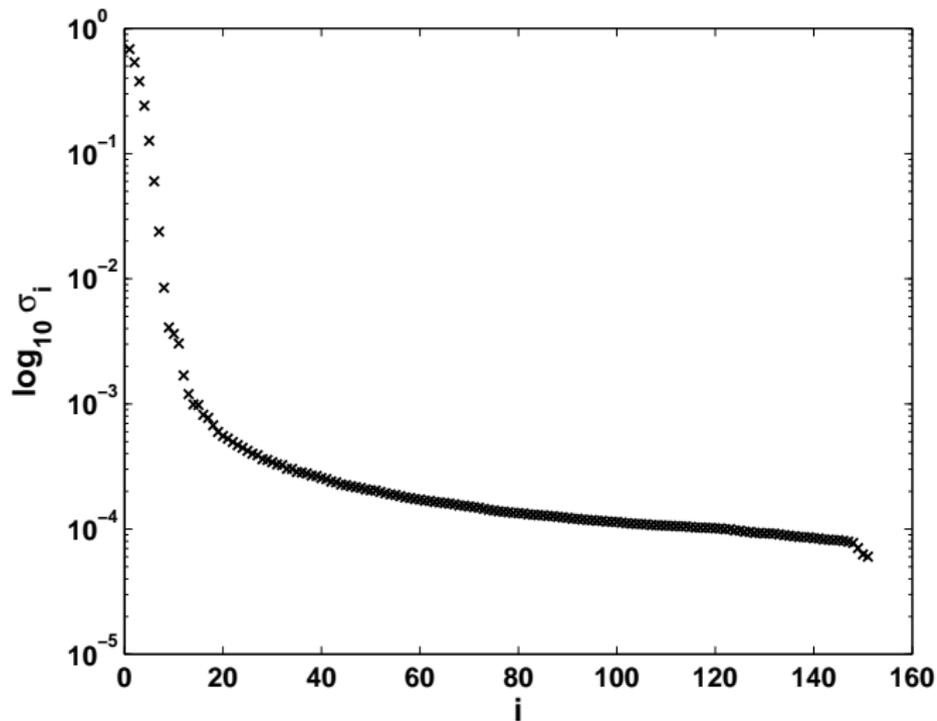


(c)  $\mathbf{v}_{40}$

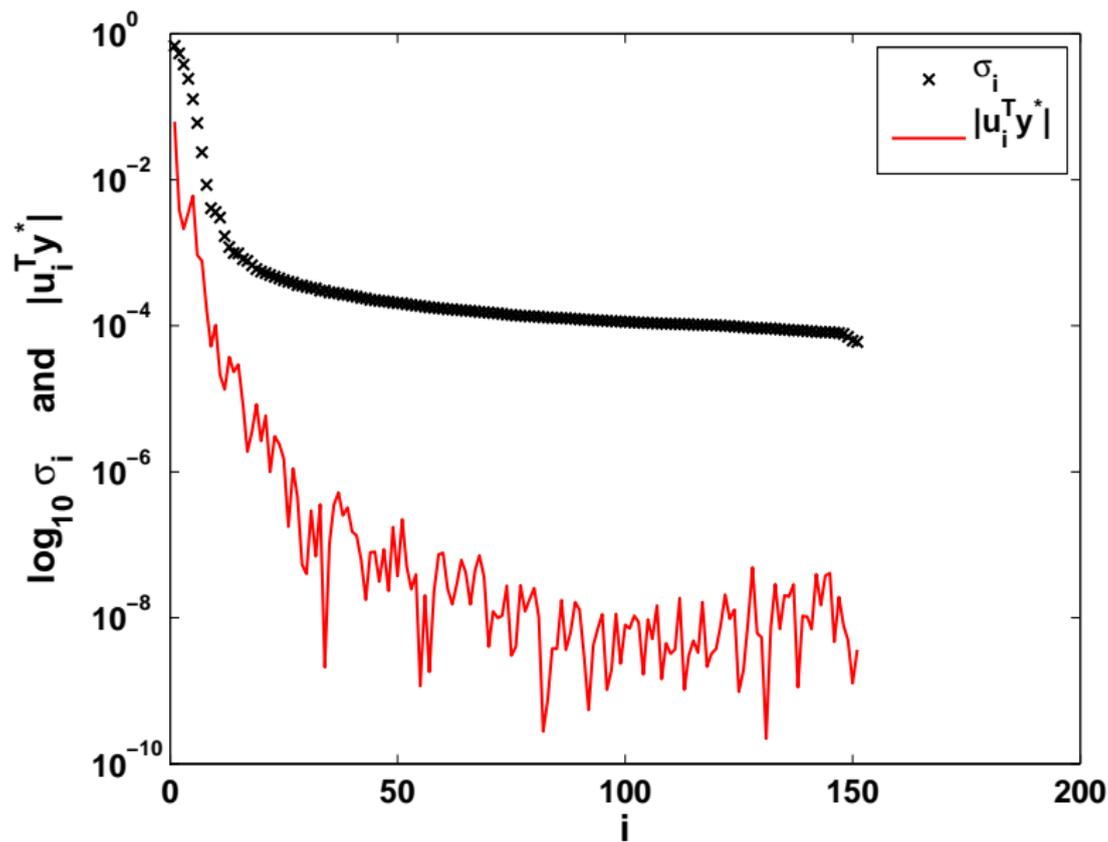


(d)  $\mathbf{v}_{120}$

## Singular Values, $\sigma_j$



# The Discrete Picard Condition



# Truncated Solution $V^T \mathbf{x} = \mathbf{z}$ (Rust and O'Leary, [8], [9])

## SVD Least-Squares Solution

From SVD solution,

$$V^T \hat{\mathbf{x}} = \Sigma^{-1} U_1^T \mathbf{b}, \quad \therefore \hat{\mathbf{x}} = V \mathbf{z} \quad (13)$$

## Truncated SVD Equation

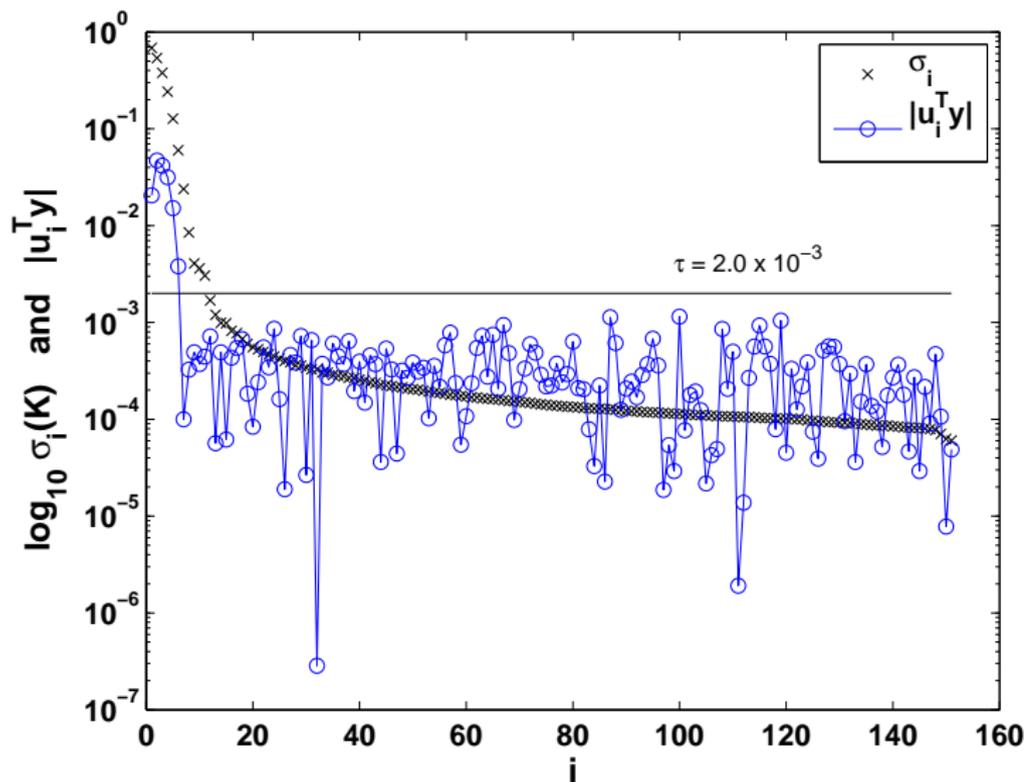
$$(V^T \tilde{\mathbf{x}})_i = \begin{cases} \frac{(\mathbf{u}_i^T \mathbf{b})}{\sigma_i}, & \text{if } |\mathbf{u}_i^T \mathbf{b}| > \tau \\ 0, & \text{otherwise,} \end{cases} \quad (14)$$

$$i = 1, 2, \dots, n$$

## Truncated SVD Solution

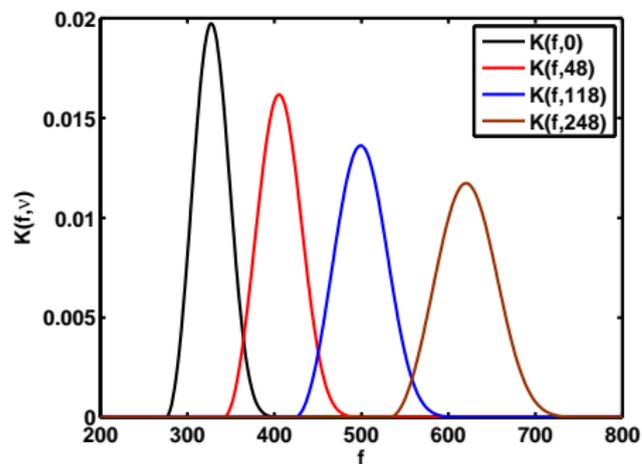
$$V^T \tilde{\mathbf{x}} = \Sigma^{-1} \tilde{U}_1^T \mathbf{b} \quad (15)$$

# Truncating $|U^T \mathbf{b}|$

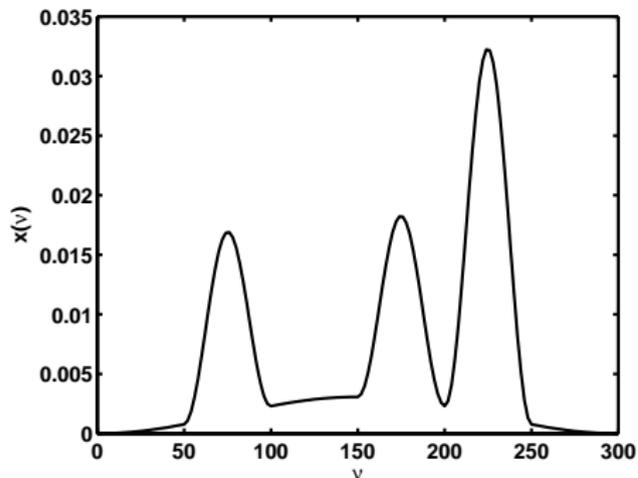


# TSVD for Test Problem

$K$  matrix

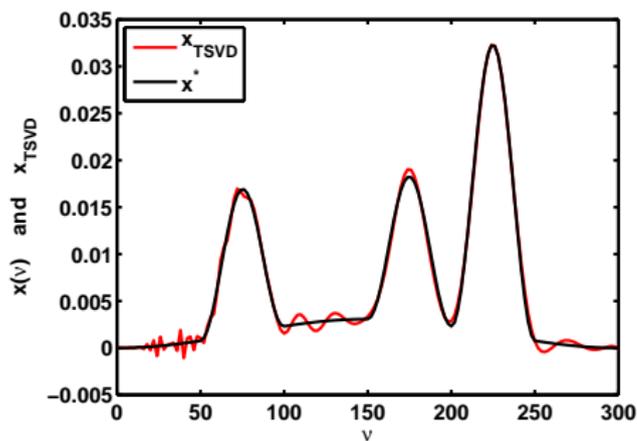


$x^*$  "true solution"

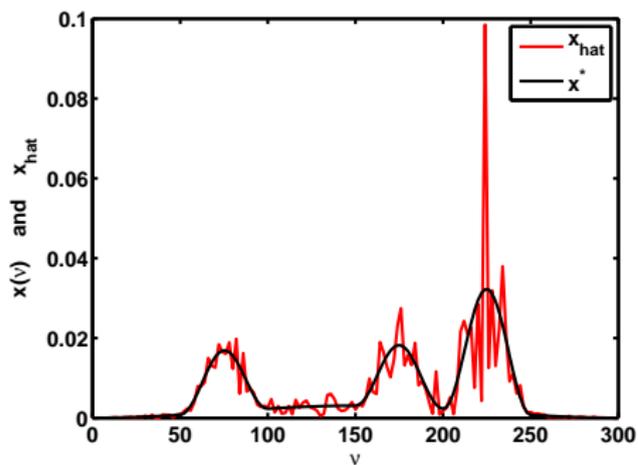


# Truncated SVD vs Constrained Minimization (FMINCON) solutions

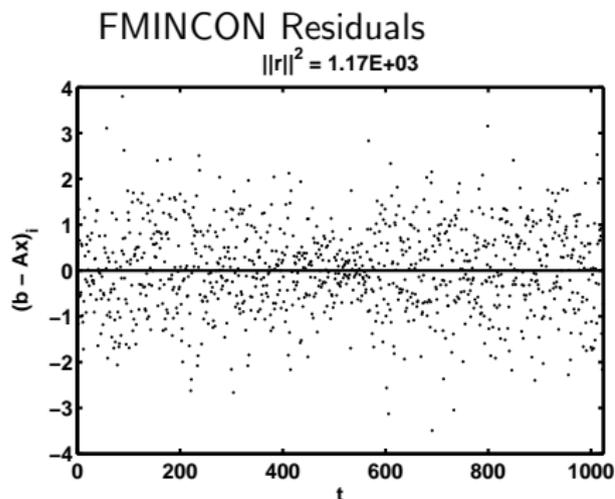
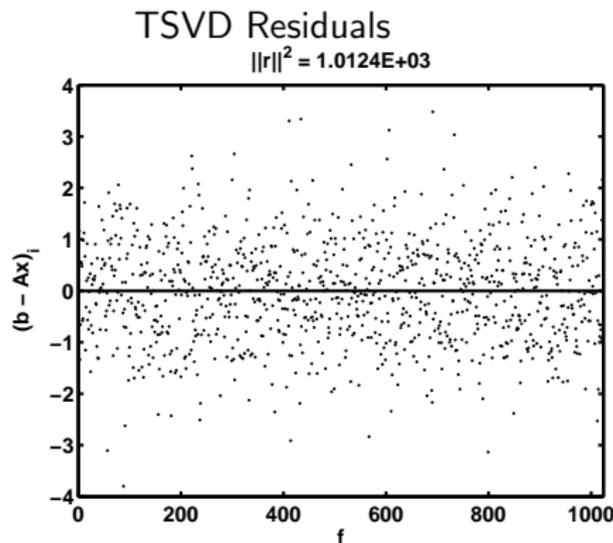
## TSVD solution



## FMINCON Solution

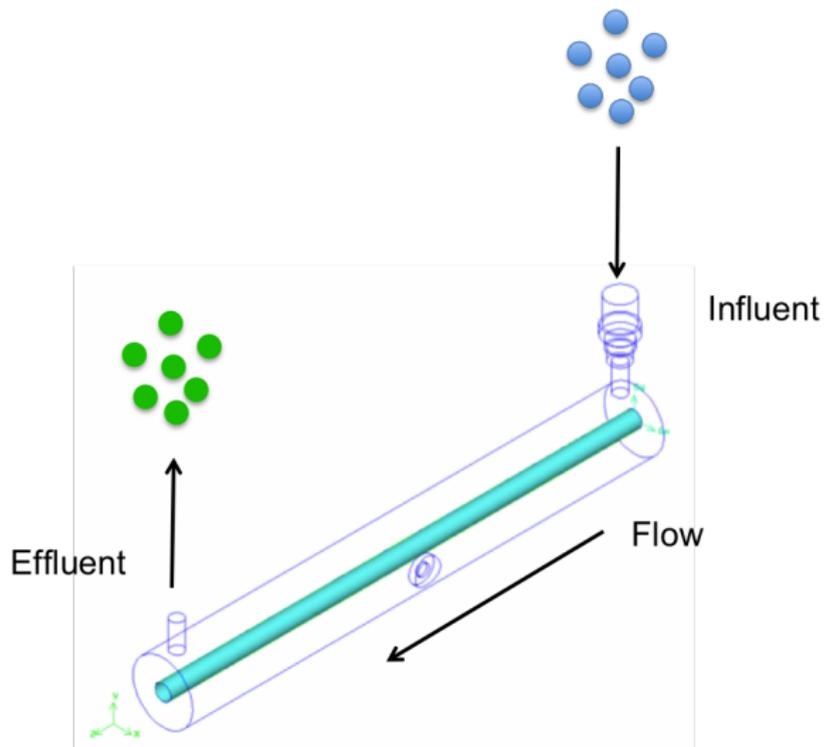


# Residual Comparison for truncated SVD and FMINCON Solns.



Recall:  $m = 1024$ ,  $\|\mathbf{b} - A\hat{\mathbf{x}}\|_2^2 \in [978.7, 1069.2]$

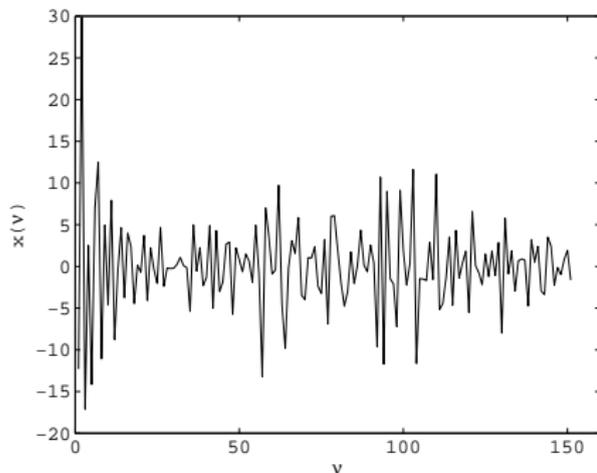
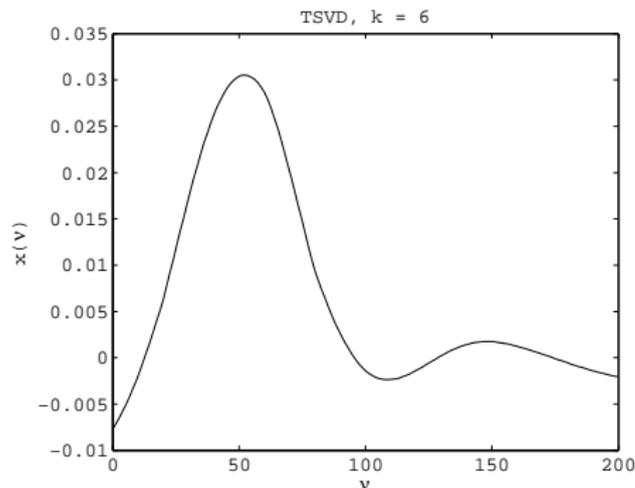
# Reactor Data



# TSVD vs Full SVD Solution: UV Reactor Data

## SVD Least-Squares Solution

$$V^T \hat{\mathbf{x}} = \Sigma^{-1} U_1^T \mathbf{b}, \quad \therefore \hat{\mathbf{x}} = V \mathbf{z} \quad (16)$$



# Background for Constrained TSVD

After Truncation

$$V^T \tilde{\mathbf{x}} = \Sigma^{-1} \tilde{U}_1^T \mathbf{b}, \quad (17)$$

if  $\tilde{\mathbf{z}} := \Sigma^{-1} \tilde{U}_1^T \mathbf{b}$  then one obtains an  $n \times n$  linear system,

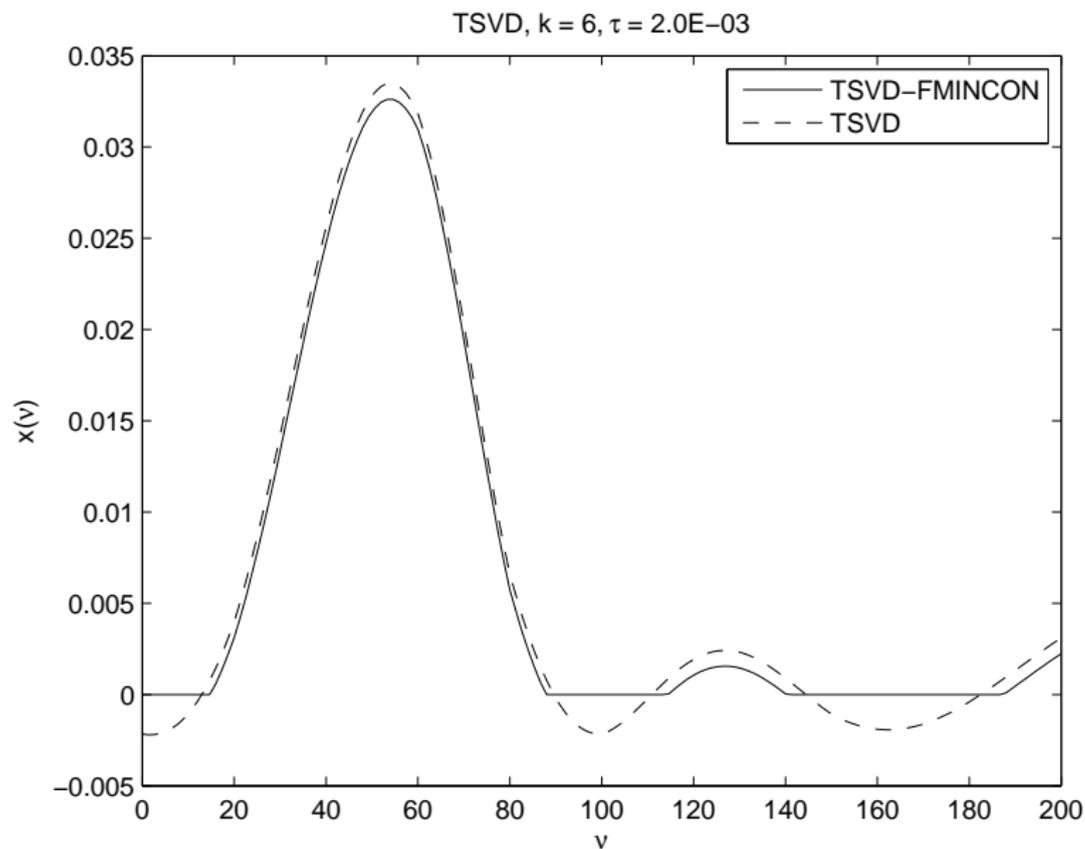
$$V^T \tilde{\mathbf{x}} = \tilde{\mathbf{z}} \quad (18)$$

New Minimization Problem

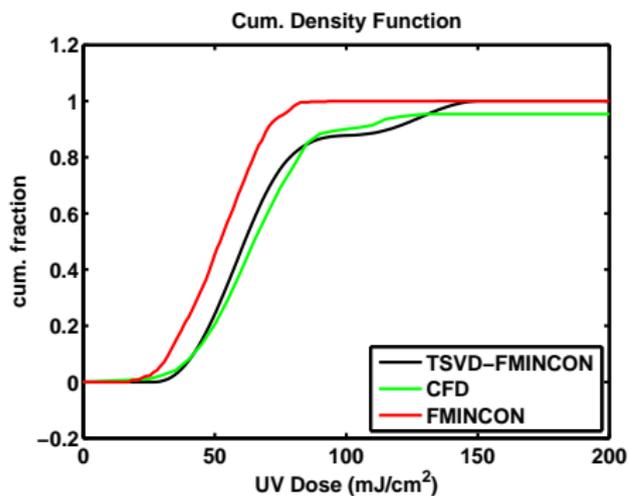
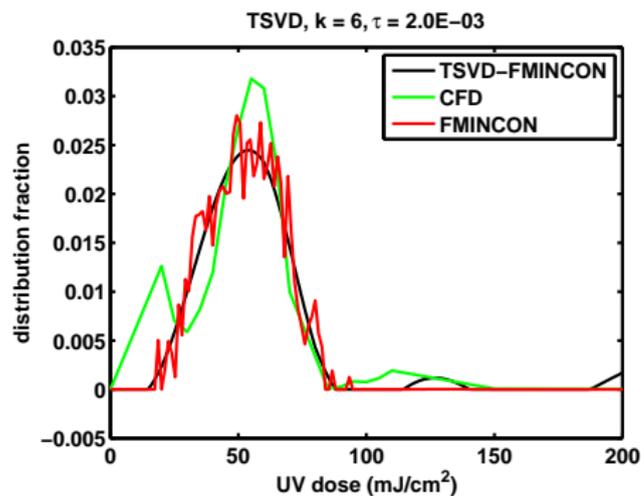
$$\varphi = \min_{\bar{\mathbf{x}} \geq 0} \|\tilde{\mathbf{z}} - V^T \bar{\mathbf{x}}\|_2^2, \quad \text{subject to } \mathbf{e}^T \bar{\mathbf{x}} = 1, \quad (19)$$

Since Eqn. was solved by FMINCON, Constrained TSVD scheme is TSVD-FMINCON

# TSVD-FMINCON Solution



# Bench Scale Reactor: TSVD-FMINCON vs. CFD-I and FMINCON



# Large Scale Reactors Tested

Matrix	Operating Conditions, $y$
TROJAN_102308	1 (A, B, C) - 9 (A, B, C)
WEDECO_111307	1 (A, B, C) - 5 (A, B, C)

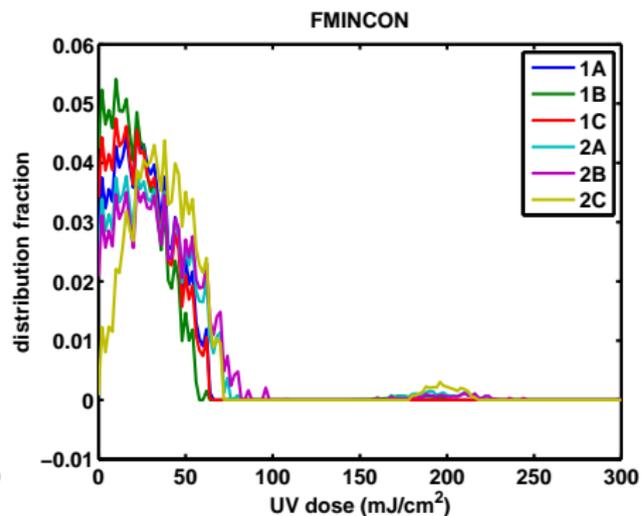
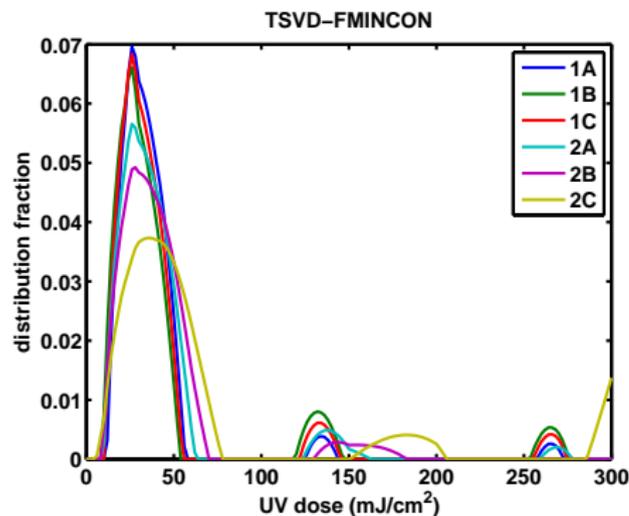
Trojan Reactor



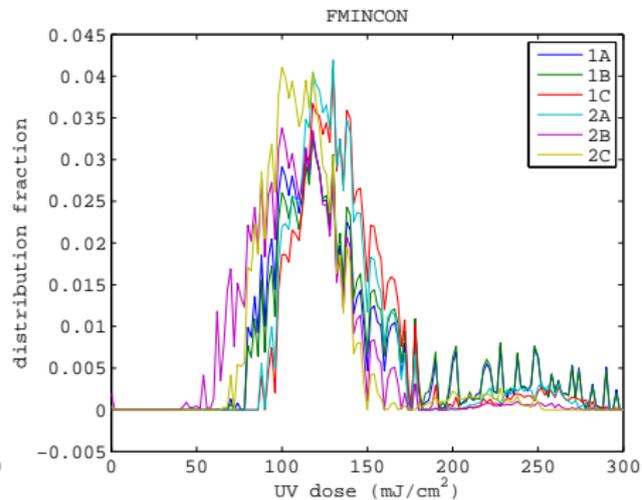
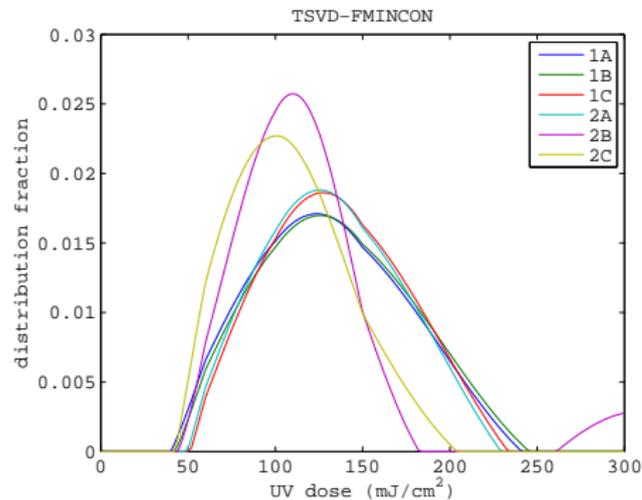
Wedeco Reactor



# TROJAN102308: TSVD-FMINCON vs. FMINCON Dose Distributions

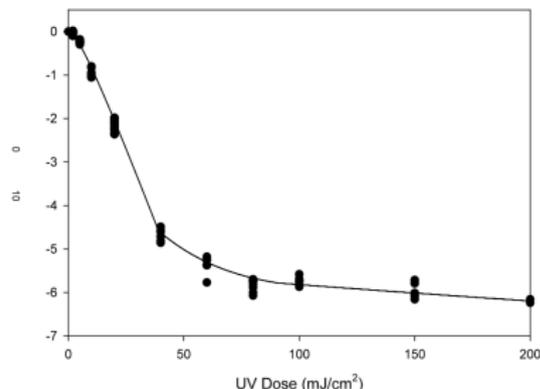
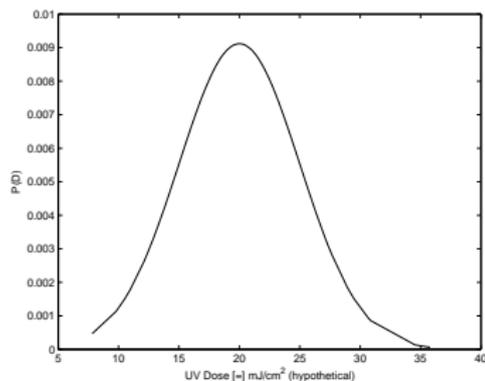


# WEDECO111307: TSVD-FMINCON vs. FMINCON



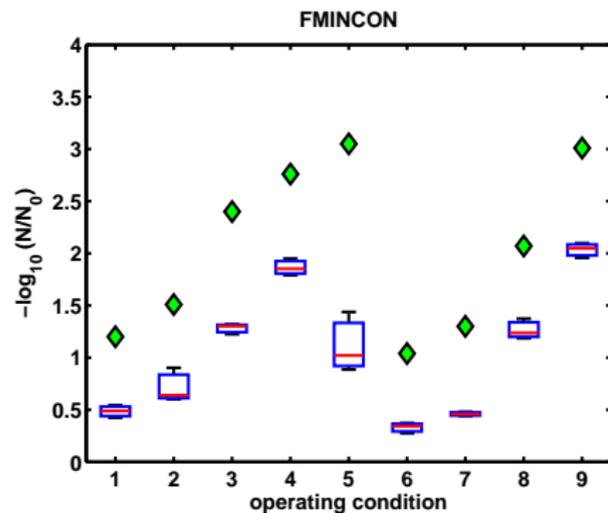
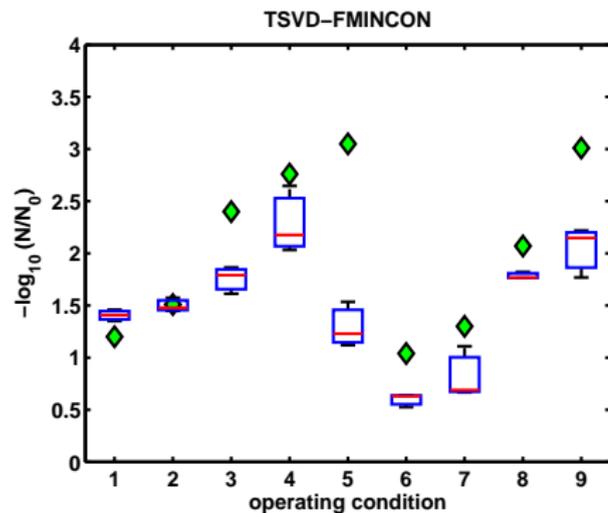
# LA: Prediction of Microbial Inactivation

- ▶ For disinfection purposes microbial inactivation predictions are used...

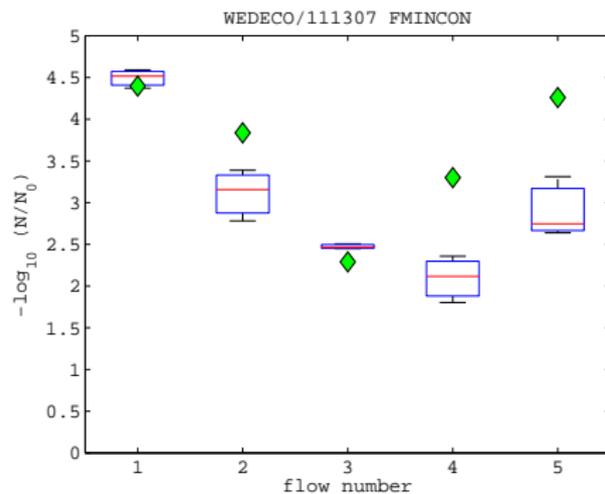
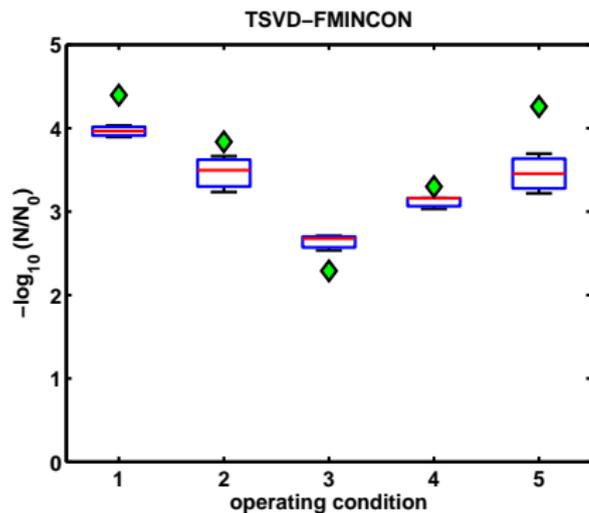


$$\left(\frac{N}{N_0}\right)_{\text{Reactor}} \approx \sum_{j=1}^n \left(\frac{N}{N_0}\right)_{\text{batch},j} \cdot P_j(D_j) \cdot \Delta D_j$$

# TROJAN102308: Log inactivation predictions MS2



# WEDECO111307: Log inactivation predictions MS-2



# Summary

- ▶ SVD leads to the verification that the LA problem shared characteristics common to ill-posed problems.
- ▶ The constrained truncated SVD (TSVD-FMINCON) scheme reduced noise in dose distributions, spurious zero-dose contributions, and for most reactor tests it provided better microbial inactivation predictions when compared to the “historical” method.

# Acknowledgments

- ▶ Partial Funding: NYSERDA, WRF
- ▶ Data provided by HydroQual, Inc. UV Validation Research Center (C. Shen, and K. Scheible)

## Questions

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